# The Influence of Motivation on Evidence Assimilation

# in a Controlled Judgement Task

by

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ABSTRACT

Prior research suggests that people ignore evidence that is inconsistent with what they want to believe. However, this research on motivated reasoning has focused on how people reason about familiar topics and in situations where the evidence presented interacts with strongly-held prior beliefs (e.g., the effectiveness of the death penalty as a crime deterrent). This makes it difficult to objectively assess how biased people are in motivated-reasoning contexts. Indeed, recent work by Jern and colleagues (2014) suggests that apparent instances of motivated reasoning may actually be instances of rational belief-updating. Inspired by this new account, the current studies reexamined motivated reasoning using a controlled categorization task and tested whether people assimilate evidence differently when they are motivated to maintain a certain belief versus when they are not. Contrary to earlier research on motivated reasoning, six studies with children and adults ($N$ = 1380) suggest that participants' motivations did not affect their information search and their beliefs were driven primarily by the evidence, even when the evidence was incongruent with their motivations. This work provides initial evidence for the account proposed by Jern and colleagues.

*Keywords*: motivated reasoning, evidence assimilation, belief-updating, information-seeking.

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# Introduction

There is widespread consensus in the scientific community that climate change is exacerbated by human activities. Yet, a recent Gallup poll indicated that almost 35% of Americans believe climate change is unrelated to manmade activities (Brenan & Saad, 2018). How do so many people hold beliefs that are inconsistent with empirical evidence? Four decades of research have established that psychological, political, cultural, and sociological aspects contribute to the beliefs people form and how these factors influence the way they process information (e.g., Alker & Poppen, 1973; Emler, Renwick, & Malone, 1983; Fishkin, Keniston, McKinnon, & Lanzetta, 1973; Hickling & Wellman, 2001; Killen & Stangor, 2001; Schult & Wellman, 1997; Shweder, Mahapatra, & Miller, 1987; Shweder & Sullivan, 1993; Wellman & Gelman, 1998). The factors influencing belief formation are multiple, but a cross-cutting theme in this literature is that people hold onto their beliefs in the face of inconsistent evidence by ignoring or reinterpreting evidence in a way that supports what they think (e.g., Babcock & Loewenstein, 1997; Dawson, Gilovich, & Regan, 2002; Ditto, Liu, Clark, Wojcik, Chen, Grady, Celniker, Zinger, 2018; Gilovich, 1983; Hastorf & Cantril, 1954; Kunda, 1990; Zuckerman, 1979). Indeed, much past research has found that people often hold biased views about propositions that they are motivated to maintain (Kunda, 1990; Klaczynski, 2000; Lord, Ross, & Lepper, 1979; West & Kenny, 2011) and that these effects are pervasive—even practicing scientists who are aware of the impact of motivation on their beliefs succumb to these tendencies (e.g., Simmons, Nelson, & Simonsohn, 2011). That is, people with opposing prior beliefs often succumb to belief polarization—they tend to strengthen prior beliefs after observing the same data (Lord, et al., 1979).

One psychological mechanism underlying belief polarization is motivated reasoning—the notion that our goals and motives affect our beliefs, attitudes, evaluations of evidence, and decision-making. Motivated reasoning also affects how people assimilate evidence and can prevent or promote belief change, particularly in situations where people are highly invested in holding onto a certain belief. This phenomenon has been widely studied because it is highly relevant in a real-world context (Epley & Gilovich, 2016; Gilovich & Ross, 2015; Lord et al., 1979; Pronin, Gilovich, & Ross 2004). For instance, after the H1N1 influenza epidemic, people became skeptical about the effectiveness of vaccines and many parents decided against vaccinating their children despite knowing about many vaccine-related healthcare successes, such as the eradication of smallpox. In fact, a study with around 15,000 children found that 6.1% children remained unvaccinated and that 74% of the parents whose children were unvaccinated stated that they consciously decided against vaccinating their child (Pearce, Law, Elliman, Cole, & Bedford, 2008). Here, parents were motivated to protect their children and an anti-vaccination attitude was rationally aligned with that motive. However, the search and evaluation of information was biased due to people's motivation to be "good parents." Such large-scale impact of motivated reasoning in the face of scientific evidence suggests that there is an incomplete understanding of all the aspects affecting people's decisions and that traditional assumptions (e.g., that people might have an information deficit, might lack access to the facts, or may be misinformed) provide only partial insight about the underlying processes involved in people's reasoning.

Motivated reasoning studies have largely focused on interpreting strongly-held beliefs that are inextricably linked to aspects of people's identity (e.g., beliefs about politics, religion, morality). Though studying people's beliefs about these topics provides a naturalistic test of the impact of motivation on reasoning, it also obscures the mechanisms underlying how people process and reason on the basis of new information. The very nature of the beliefs (e.g., beliefs about climate change) and evidence (e.g., scientific consensus) in question makes it difficult to *quantify* the extent to which motivation impacts people's beliefs. For instance, what is the relevant evidence for climate change and how should we quantify it? Once quantified, a principled mathematical benchmark also needs to be assumed to properly understand the extent to which motivation biases people's reasoning. Many researchers now argue that once a normative standard is articulated, it appears that people are more "in tune" with the evidence than it might initially appear. For example, Jern and colleagues (2014) state that the normative standard for reasoning under uncertainty is usually based on probabilistic inference—if one reasons according to the axioms of probability, seemingly irrational decisions appear rationally aligned (Griffiths & Tenenbaum, 2006; Tenenbaum, Griffiths, & Kemp, 2006; Vul, Goodman, Griffiths, & Tenenbaum, 2014; Zimper & Ludwig, 2009). Assuming such normative standards to assess behavior can help interpret the reasoning behind people's choices: If we are able to determine the strength of a person's political beliefs, we might be able to estimate the probability that they support or oppose important issues such as climate change (Hornsey, Harris, Bain, & Fielding, 2016). Hence, purported instances of motivated reasoning might often stem from coherent belief networks (e.g., Gershman, 2018; Jern, Chang, & Kemp, 2014).

The Bayesian view of cognition also assumes that people's decisions stem from coherent belief networks and that people can make decisions in an optimal way given ambiguous evidence. Further, Bayesianism often explains cognitive processes using probability theory (see Jones & Love, 2011) and provides a rational interpretation of people's decisions under uncertainty. Adopting a rational view of decision-making can potentially help explain complex aspects of human cognition, such as motivated reasoning, since such a view establishes a benchmark against which people's decisions can be examined (for instance, that people make decisions according to probability theory). Hence, we sought to understand the mechanisms behind motivated reasoning using a controlled judgement task. In the following sections, we discuss the influence of motivation on evidence assimilation using a structured task (Experiments 1, 2, 3) and the development of evidence assimilation in a motivated-reasoning context (Experiments 4, 5, 6).

## Motivated Reasoning in a Structured Task

Our aim was to determine whether people are biased in their reasoning when they are motivated to maintain a certain belief. Specifically, we wanted to quantify the extent to which motivation affects reasoning when there is ambiguous evidence supporting a belief that people are motivated to maintain. To this end, we created a simple categorization task to test whether people were biased in their choices when the evidence was inconsistent with a desired outcome. We used a structured task to control for external factors affecting people's reasoning and manipulate the effect of motivation on their choices.

## Experiment 1

### Procedure

Participants were shown two pages and then given some hints about the pages. Their task was to use the hints to categorize which page belonged to a novel category (for instance, a "Platome") in a self-paced task. Hints were presented sequentially—for instance, the first hint was, "The Platome might be the one with two black circles in the top row," followed by the next hint that said, "The Platome might be the one with no black triangles," and so forth (see Figure 1). All trials contained a total of six hints and after all the hints were presented in a trial, participants were asked the categorization question (e.g., "Which one is the Platome?"). The reader is encouraged to view a speeded clip of one trial in the experiment here. After making their categorization judgment, participants were also asked to report (on a scale of 0 to 6) the number of hints they remembered in support of the "bonus page", which was indicated by a blue border. They were told that the reward associated with selecting the bonus page as the correct response would be larger than the reward for choosing the other page. We describe this reward structure in more detail below.

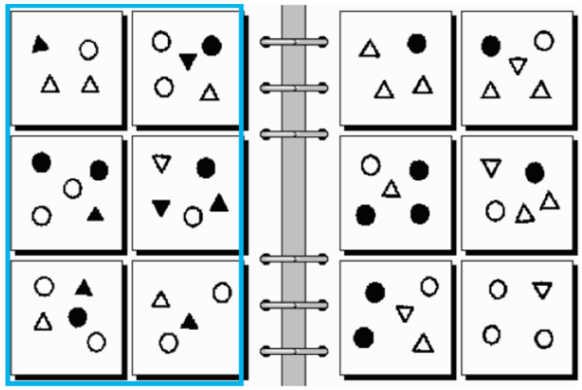

*Figure 1.* An example of the binder images used in Experiment 1, 2, and 3. The "bonus page" is indicated by the blue border.

**Reward Structure.** In order to quantify the effect of motivation on people's reasoning, we manipulated the reward associated with choosing either the left or right page in the binder. Prior work suggests that people are motivated to be better than average about socially desirable traits (Brown, 2012), so we told participants that scoring higher points in this task meant they had better "attentional control than their peers." Points were assigned differently for choosing the bonus page versus the other page as the correct response—this was our attempt to motivate participants to win more points in this task. That is, participants were instructed that 1) they would win one point for choosing the correct response, 2) if the correct response *happened to be* the page with the blue border (and they chose it), then they would win two bonus points, and 3) that they would win no points for incorrect responses. Participants were not given any feedback about their choices and were told they would find out at the end of the study if their choice was correct. Next, in order to pit their motivations against their desire to win more points, we developed three conditions wherein we manipulated the hints supporting the bonus page.

**Conditions.** We created three conditions with different distributions of hints in a within-subjects design to see the extent to which ambiguous evidence would influence participants' choices in this task. The hints were distributed such that they either supported or did not support the bonus page. In the Half condition, three of six hints supported the hypothesis that the bonus page was the correct response. That is, they received ambiguous evidence supporting the bonus page in the Half condition. In the Little condition, only one of six hints supported the hypothesis that the bonus page was the correct response. In the None condition, no hints supported the hypothesis that the bonus page was the correct response. Hence, in the Little and None conditions, they received evidence that generally opposed the bonus page.

**Memory.** As noted above, we also examined participants' memory for the hints presented in each condition to determine whether false memory was a factor influencing their choices. The response scale for this question ranged from 0 to 6, representing the total number of hints presented within each trial.

## Hypotheses

To assess the extent to which motivation affected participants' responses, we first manipulated the number of hints that supported the belief that the bonus page was the correct response, then observed how this manipulation impacted their choices. In the Little and None conditions, we hypothesized that participants would follow the evidence and choose accordingly as the evidence was unambiguous in both those conditions. Of particular interest were the mechanisms behind participants' responses in the Half condition wherein we hypothesized that participants would want to maximize their reward by choosing the bonus page more often. We hypothesized that participants' memory would be inaccurate and that this would influence their choices within our task.

## Preregistration and Analytic Approach

The sample size, predictions, and analysis scripts of our study were preregistered on the Open Science Framework. We conducted a power analysis to determine the sample size required to detect a Cohen's *d* of .15, which was the smallest effect size we cared to detect. To this end, we collected 350 participants from Amazon's Mechanical Turk. We tested our hypotheses using Bayesian mixed-effects modeling with the R package brms (Bürkner, 2017). We set regularizing priors for all population-level effects in our models: namely, a normal distribution with a mean of 0 (i.e., no effect) and a standard deviation of 1. These priors are recommended because they provide conservative effect size estimates and reduce the likelihood of overfitting (Gelman, Lee, & Guo, 2015; McElreath, 2016).

## Results

We sought to test whether participants would exhibit motivated reasoning in a controlled task; in this case, scoring higher points meant that they were better than their peers. To test our hypotheses, we performed logistic regression predicting participants' responses (1 = Chose bonus picture; 0 = Did not choose bonus picture) based on Evidence (Reference = Half condition). This model included a group-level effect of Subject and allowed for heterogeneity in the slope of the effect of evidence on participants' responses. Our model is specified below in the syntax of lme4 (Bates, Mächler, Bolker, & Walker, 2015):

```
Response ~ 0 + intercept + Evidence + (1 + Evidence| Subject)
```

Bayesian analyses formulate model parameters as probability distributions wherein the posterior distribution for a parameter theta ($\theta$) is computed via the prior and likelihood of $\theta$. To model the joint probability distribution of participants' responses, we specified the following priors over the possible effects each variable could have on our response variable:

$\beta_0 \sim N(0, .75)$

$\beta_{None} \sim N(-2.19, .5)$

$\beta_{Little} \sim N(-2.19, .5)$

$sd_{\forall_x} \sim N(1, 3)$ where *x* is a group-level effect

$\Omega_{\mathbf{k}} \sim LKJ(1)$ where $\Omega_{\mathbf{k}}$ is a correlation matrix for group-level parameters which assumes all correlation matrices are equally likely.

The posterior regression coefficients for this analysis represent participants' responses across conditions and are shown in Figure 2 below.

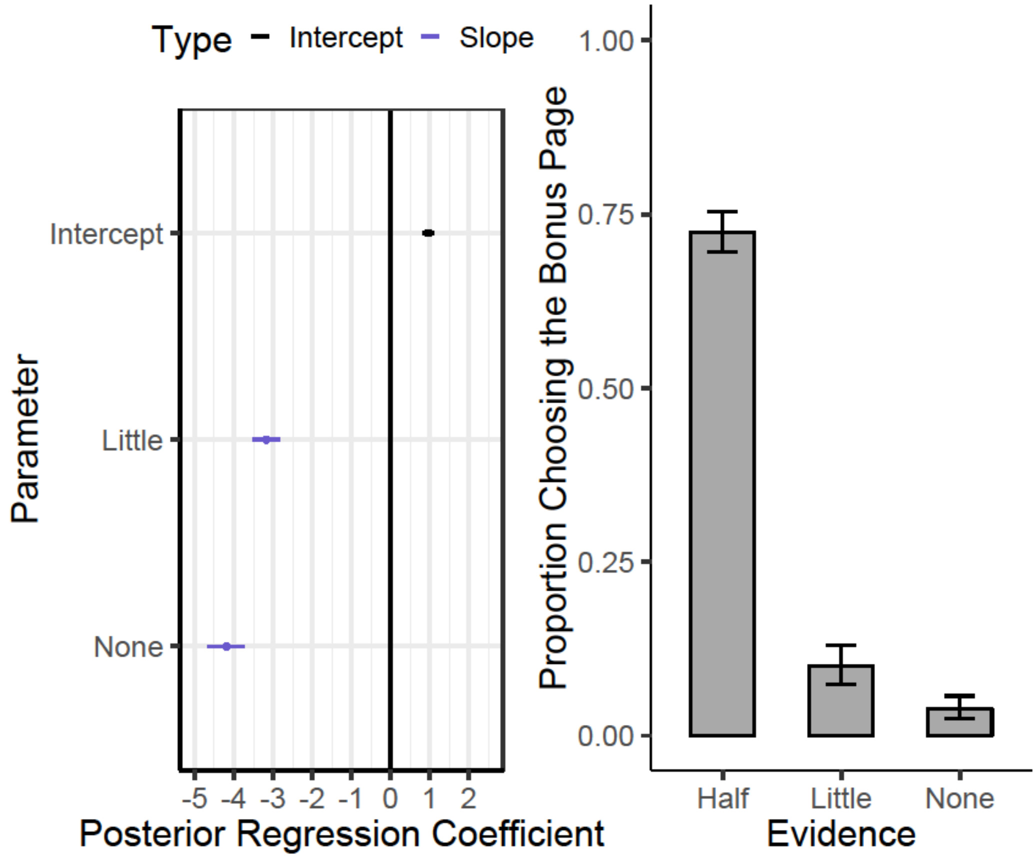


*Figure 2.* The posterior regression coefficients (left) and a bar graph (right) of the proposition of choosing the bonus page across conditions in Experiment 1. Relative to the Half condition, participants chose the bonus page less often in the other two conditions.

These results indicated some evidence for biased reasoning in the Half and Little conditions. We also found that participants chose the bonus page as the correct response more often in the Half condition even though the evidence supporting that conclusion was ambiguous (see Figure 2 below). This supports our preregistered hypothesis that participants would select the bonus page more often when the hints ambiguously supported that page.

Further, we hypothesized that participants' memory for the hints presented would affect their choices. We tested this by performing ordinal regression predicting memory for the bonus page (0 = No hints supporting the bonus page; 3 = Three hints supporting the bonus page; 6 = Six hints supporting the bonus page) based on condition (Reference = Half condition). This model included a group-level effect of Subject and allowed for heterogeneity in the slope of the effect of evidence on participants' memory. Our model is specified below in the syntax of lme4 (Bates et al., 2015):

```
Memory ~ Evidence + (1 + Evidence|Subject)
```

To model the joint probability distribution of participants' responses, we specified the following priors over the possible effects each variable could have on our response variable:

$\beta_{Intercept[1]} \sim N(-2.19, .5)$

$\beta_{Intercept[2]} \sim N(-1.38, .5)$

$\beta_{Intercept[3]} \sim N(-.61, .5)$

$\beta_{Intercept[4]} \sim N(.61, .5)$

$\beta_{Intercept[5]} \sim N(1.38, .5)$

$\beta_{Intercept[6]} \sim N(2.19, .5)$

$\beta_{None} \sim N(-1, 1)$

$\beta_{Little} \sim N(-1, 1)$

$sd_{\forall_x} \sim N(1, 3)$ where $x$ is a group-level effect

$\Omega_{\mathbf{k}} \sim LKJ(1)$ where $\Omega_{\mathbf{k}}$ is a correlation matrix for group-level parameters which assumes all correlation matrices are equally likely.

The posterior regression coefficients for this analysis represent participants' responses to the memory question across conditions and are shown in Figure 3 below. We found that participants systematically misremembered the amount of hints presented in this task across all conditions. That is, participants remembered about one hint more than was actually presented in support of the bonus page and this was further evidence for the motivated-reasoning hypothesis since participants wanted to win more points and tended to misremember the hints supporting the bonus page.

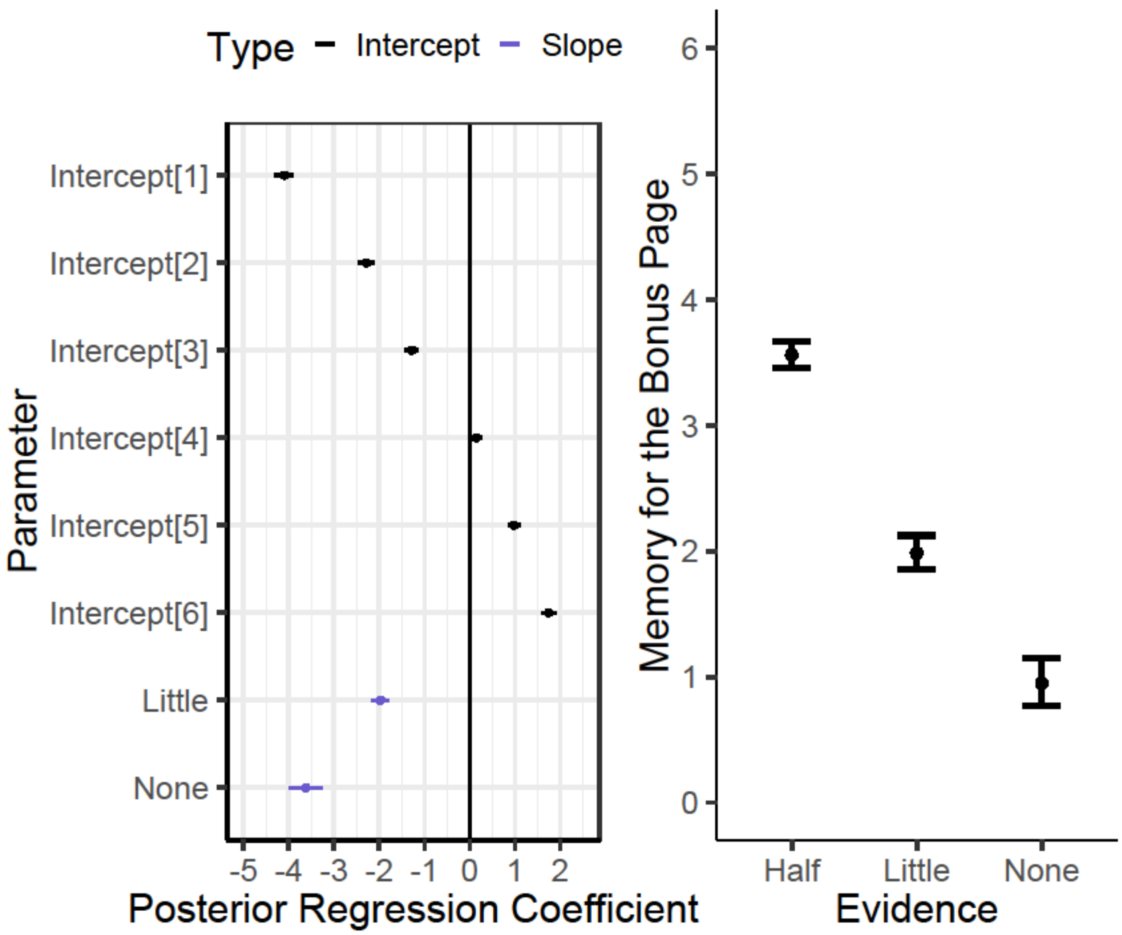


*Figure 3.* The posterior regression coefficients (left) and a marginal-effects plot (right) of participants' memory for the bonus page across all conditions in Experiment 1. Participants remembered about one hint more than was actually presented across all conditions.

These analyses suggest that participants' motivations affected their choices when the hints ambiguously supported the bonus page and even when there was a single piece of evidence supporting the bonus page, but not when there was no evidence supporting that page. Further, memory for the amount of hints presented was biased towards the bonus page, a finding which may indicate the effect of motivated reasoning on participants' decisions. However, it is possible that participants were maximizing utility in their choices in the Half condition—given two choices with equal evidence and one of those choices resulting in a larger reward, participants *should* choose to win a larger reward. To explore this possibility and to replicate our findings in Experiment 1, we conducted another study using a modified version of our categorization task.

## Experiment 2

Were participants biased in Experiment 1 or were they making decisions that maximized utility? To answer this question, we changed two aspects of the categorization task used in Experiment 1. First, to determine the effect of motivation on participants' responses, we added a control condition (i.e., a condition in which there was no motivation to choose one page or another) and compared their choices and memory given the presence or absence of motivation. If participants systematically misremember evidence for the bonus page in the Motivation condition compared to the Control condition, this might demonstrate that participants are exhibiting clear signs of motivation reasoning in a controlled task. Second, we replaced the trials where no hints supported the bonus page (the None condition) with trials where five of six hints supported the bonus page (the Most condition). We did this to further confirm that participants were following the evidence correctly. Hence, this experiment had a 2 (Motivation condition, Control condition) × 3 (Half condition, Little condition, Most condition) within-subjects design. An example of a trial from the Motivation condition can be found here and from the Control condition can be found here.

### Hypotheses

In light of the findings from Experiment 1, we hypothesized that we would replicate our findings in the Half condition—participants would pick the bonus page above what the evidence supported to maximize their reward. In the Little and Most conditions, we hypothesized that participants would follow the evidence and choose accordingly—they would pick the bonus page more often in the Most condition and less often in the Little condition. In contrast, because there was no motivation for participants to pick either of the pages more often in the Control condition, we hypothesized that they would follow the hints presented and choose accordingly across all trials. Consequently, we predicted participants would choose at chance in the Half condition.

We also hypothesized that participants' memory would be inaccurate and that this would influence their choices within the task. We predicted that participants would misremember the hints presented across conditions but were unsure whether misremembering would be more systematic in the Motivation condition compared to the Control condition.

**Preregistration and Analytic Approach**

The sample size, predictions, and analysis scripts of our study were preregistered on the Open Science Framework. We conducted a power analysis to determine the sample size required to detect a Cohen's *d* of .15 and so collected 350 participants from Amazon's Mechanical Turk. The analytic approach was similar to Experiment 1.

**Results**

We wanted to examine whether participants would make different choices when they had a chance to win bonus points (Motivation condition) versus when they did not (Control condition) and the extent to which the presence of a motivating factor would systematically affect their memory. We first performed logistic regression predicting participant's responses (1 = Chose bonus picture; 0 = Did not choose bonus picture) based on Evidence (Half, Little, Most), Condition (Motivation or Control) and their interaction (Reference = Half-Motivation condition). This model included a group-level effect of Subject and allowed for heterogeneity in the slope of the interaction on participants' responses. Our model is specified below in the syntax of lme4 (Bates et al., 2015):

```
Response ~ 0 + intercept + Evidence*Condition +
(1 + Evidence*Condition|Subject)
```

To model the joint probability distribution of participants' responses, we specified the following priors over the possible effects each variable could have on our response variable:

$\beta_0 \sim N(0, .75)$

$\beta_{Little} \sim N(-2.19, .5)$

$\beta_{Most} \sim N(2.19, .5)$

$\beta_{NoMotivation} \sim N(0, .5)$

$\beta_{Little \times NoMotivation} \sim N(0, .5)$

$\beta_{Most \times NoMotivation} \sim N(0, .5)$

$sd_{\forall_x} \sim N(1, 3)$ where *x* is a group-level effect

$\Omega_{\mathbf{k}} \sim LKJ(1)$ where $\Omega_{\mathbf{k}}$ is a correlation matrix for group-level parameters which assumes all correlation matrices are equally likely.

The posterior regression coefficients for this analysis represent participants' responses across conditions and are shown in Figure 4 below.

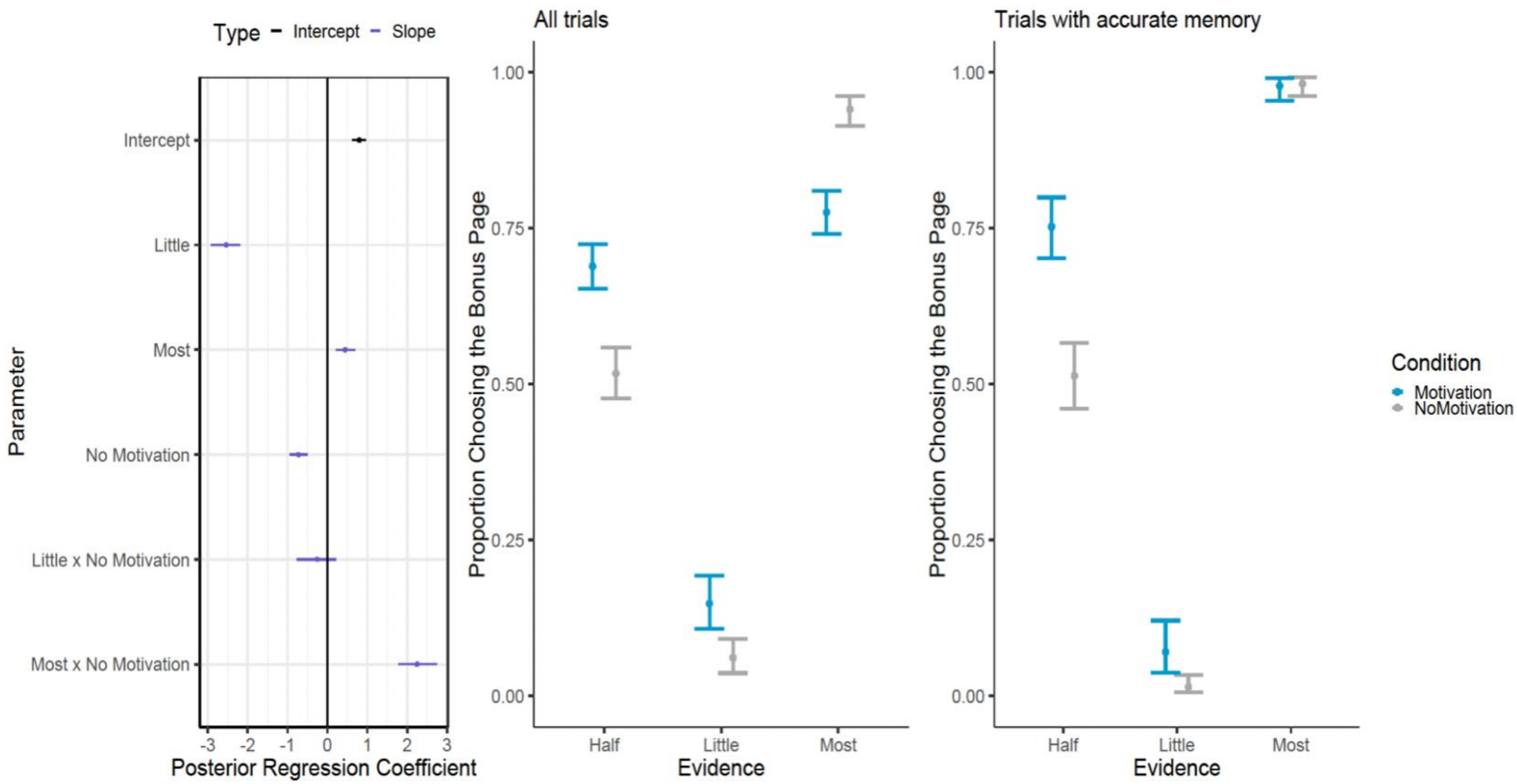


*Figure 4.* The posterior regression coefficients (left) and a marginal-effects plot (right) of the proportion of choices for the bonus page across conditions in Experiment 2. Error bars represent 95% credible intervals. We mainly compared participants' responses in the Motivation condition to the Control condition. Participants chose the bonus page more often in the Little and Half conditions in the Motivation condition compared to the Control condition. However, participants who accurately reported the hints presented still chose the bonus page more often when the evidence was ambiguous in the Motivation condition.

Participants' performance replicated our findings from Experiment 1—they followed the hints presented but went beyond the hints to maximize their reward in the Half condition. However, puzzlingly we found that participants chose the bonus less frequently in the Most-Motivation cell relative to the Most-Control cell. Given people's memory performance was quite poor, we sought to determine whether this effect was driven by poor memory for the information presented rather than some other cognitive factor. To this end, we re-ran the same regression model predicting participant performance based on Evidence, Condition, and their interaction using only the trials in which people correctly remembered how much evidence supported a given page. This analysis revealed that, as in Experiment 1, in the Half condition, participants chose the bonus page more often in the Motivation condition but did not do so in the Control condition (see Figure 4 above). In the Little condition, participants chose the bonus page more often in the Motivation condition compared to the Control condition and this indicates some level of biased reasoning as only one hint supported the bonus page. In the Most condition, participants followed the evidence and chose based on the evidence presented and this pattern was not materially different across the Motivation and Control conditions. Hence, participants generally behaved in line with the evidence when they accurately remembered the hints presented in each condition.

To determine the extent of misremembering across conditions, we performed an ordinal regression predicting memory for the bonus page (0 = No hints supporting the bonus page; 6 = Six hints supporting the bonus page) based on Evidence, Condition, and their interaction (Reference = Half-Motivation condition). This model included a group-level effect of Subject and allowed for heterogeneity in the slope of the interaction on participants' memory. Our model is specified below in the syntax of lme4 (Bates et al., 2015):

```
Memory ~ Evidence*Condition + (1 + Evidence*Condition| Subject)
```

To model the joint probability distribution of participants' responses, we specified the following priors over the possible effects each variable could have on our response variable:

$\beta_{Intercept[1]} \sim N(-2.19, .5)$

$\beta_{Intercept[2]} \sim N(-1.38, .5)$

$\beta_{Intercept[3]} \sim N(-.61, .5)$

$\beta_{Intercept[4]} \sim N(.61, .5)$

$\beta_{Intercept[5]} \sim N(1.38, .5)$

$\beta_{Intercept[6]} \sim N(2.19, .5)$

$\beta_{Little} \sim N(-1,1)$

$\beta_{Most} \sim N(1, 1)$

$\beta_{NoMotivation} \sim N(0, 1)$

$\beta_{Little \times NoMotivation} \sim N(0, 1)$

$\beta_{Most \times NoMotivation} \sim N(0, 1)$

$sd_{\forall_x} \sim N(1, 3)$ where *x* is a group-level effect

$\Omega_{\mathbf{k}} \sim LKJ(1)$ where $\Omega_{\mathbf{k}}$ is a correlation matrix for group-level parameters which assumes all correlation matrices are equally likely.

The posterior regression coefficients for this analysis represent participants' responses to the memory question across conditions and are shown in Figure 5 below. If participants were irrationally biased by the presence of a motivating factor, then this should be reflected in a systematic tendency to misremember evidence supporting the bonus page. However, we observed no such effect. In fact, in both the Motivation and Control conditions, participants overestimated the amount of evidence for a given page in the Little condition and underestimated the amount of evidence for a given page in the Most condition. We observed this tendency regardless of condition and the initial observation—that people's memory was biased for the bonus page in Experiment 1—seems more likely to due to a bias in people's use of the response scale measuring memory than an irrational bias driven by the presence of a motivating factor.

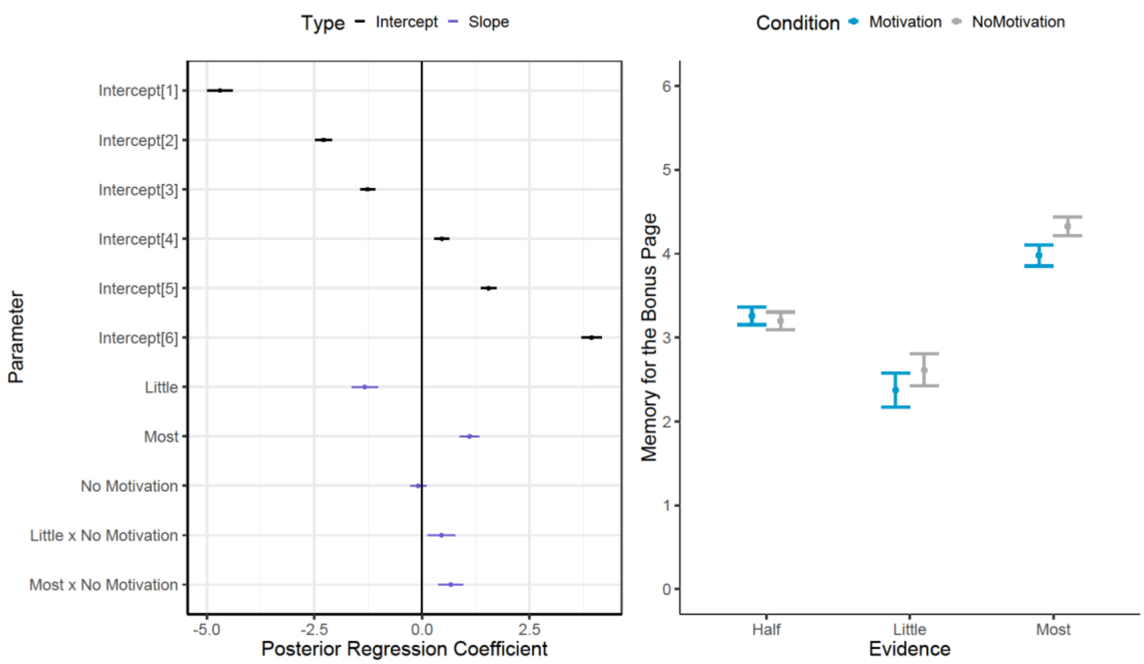


*Figure 5.* The posterior regression coefficients (left) and a marginal-effects plot (right) of participants' memory for the bonus page across conditions in Experiment 2. Error bars represent 95% credible intervals. Memory for the bonus page was generally inaccurate, but misremembering did not follow a systematic pattern across conditions.

Altogether, participants' choices under uncertainty in the Motivation condition were not entirely due to a bias in their memory because (1) in the Little and Most conditions, participants generally followed the hints presented, (2) in the Half condition, participants chose the bonus page even after they reported that there was ambiguous evidence supporting that choice, and (3) participants chose based on the evidence presented across all trials in the Control condition. These findings suggest that participants chose to maximize their reward when the evidence was ambiguous in the Motivation condition.

## Discussion: Experiments 1 and 2

In Experiments 1 and 2, we observed that participants reliably followed the evidence and that they responded based on the presence or absence of motivation when the evidence was ambiguous. However, motivated reasoning might have less to do with the way people assimilate information and more to do with the type of evidence they seek when they are motivated. Strongly-held beliefs and motivations might alter the kinds of evidence people seek in order to maintain a given belief (Golman et al., 2017; Jonas, Schulz-Hardt, Frey, & Thelen, 2001; Nickerson, 1998). Extensive work on the confirmation bias has revealed that people often fail to assimilate potentially helpful information and sometimes even go so far as to actively avoid looking at available information if it threatens their existing beliefs (see Ganguly & Tasoff, 2016). If given a chance to choose the amount of information required to decide upon a correct response, participants' responses might differ in the Motivation condition versus the Control condition within our task. To test this possibility, we ran another experiment with a modified version of the task used in Experiment 2.

## Experiment 3

Experiment 3 aimed to examine how motivation might affect the information people seek as they form a belief. We used a categorization task similar to that of Experiments 1 and 2 but made several other changes to the structure of the task. First, we simplified our design by only including a Little and Most condition. Hence, this study had a 2 (Motivation vs. Control) x 2 (Little evidence, Most evidence) within-subjects design. Participants still had to categorize the pages into a novel category (for instance, a Platome) based on the hints. However, after each hint they were given the option to receive additional information to decide the correct response. For instance, after a hint was presented, we asked participants, “Do you think you have enough information to decide which picture is a Platome?”. If they disagreed with this question, then they were given another hint. Participants received at least one hint and could then choose to receive additional hints before deciding the correct response in each trial. In total, participants could be presented with four hints in any given trial. In this way, participants decided how many hints were sufficient to answer the categorization question (“Which one is the Platome?”). They did not receive feedback after each trial but were told that they would find out if they were right at the end of the study. An example of a trial from the Motivation condition can be found here.

Second, unlike in the previous two studies, the hints supporting a given page within each trial were not randomized. In the Motivation condition, the hints supporting the bonus page always appeared *after* the hints that did not support the bonus page (see Table 1 below). The trials in the Control condition mirrored those from the Motivation condition. This aspect of the task allowed us to make a clear comparison between participants who sought information differently within the Motivation condition versus Control condition. That is, we were able to determine whether people were biased in their information search within a controlled task.

Table 1*: Distribution of evidence in the Motivation and Control Conditions across trials.*

| Condition | Motivation | Control |
|---|---|---|
| Little evidence | ✕✕✕✓ | ✕✕✕✓ |
| Most evidence | ✕✓✓✓ | ✕✓✓✓ |

Note: The x's depict hints that do not support the bonus page and the check marks represent hints that support the bonus page.

**Hypotheses**

We were particularly interested in determining the mechanisms behind participants' responses in the Motivation condition versus the Control condition. To this end, we had different hypotheses based on the conditions within this task. First, in the Little condition, we predicted that because participants received hints that did not support the bonus page first, they should stop their information search after receiving three hints. This is because this is the minimal amount of information required to make an informed choice in the task. However, if the motivated-reasoning account is correct, then they should search for more information supporting the belief that the bonus page is the correct response and seek more than two additional hints.

Second, in the Most condition, we predicted that because participants received hints that support the bonus page first, they should again stop their information search after receiving three hints because this is the minimal amount of information required to make an informed choice in this condition (see Table 1). On the other hand, if participants are biased then they should not seek more information supporting the belief that the bonus page is the correct response and seek only one additional hint.

**Preregistration and Analytic Strategy**

The sample size, predictions, and analysis scripts of our study were preregistered on the Open Science Framework. Data was collected from Amazon's Mechanical Turk. We anticipated a true effect size of Cohen's *d* of .15 in a within-subjects design. For an effect of this size, we needed 390 participants so the Type-M error rate would be no greater than 1.1 (Gelman & Carlin, 2014). However, to account for a ~ 10% drop out rate, we recruited 430 participants in total.

**Results**

We tested whether participants' search for information would differ depending on whether they were motivated to win bonus points (i.e., in the Motivation condition) versus when they were not motivated (i.e., in the Control condition). To test this, we fit an ordinal regression model predicting information sought (0 = No additional hints sought; 3 = Three additional hints sought) on the basis of Evidence (Little, Most), Condition (Motivation, Control), and their interaction (Reference = Little-Motivation condition). This model included a group-level effect of Subject and allowed for heterogeneity in the slope of the interaction on participants' responses. Our model is specified below in the syntax of lme4 (Bates et al., 2015):

```
InformationSought ~ Evidence*Condition +
(1 + Evidence*Condition|Subject)
```

To model the joint probability distribution of participants' responses, we specified the following priors over the possible effects each variable could have on our response variable:

$\beta_{Intercept[1]} \sim N(-2.19, .5)$

$\beta_{Intercept[2]} \sim N(0, .5)$

$\beta_{Intercept[3]} \sim N(2.19, .5)$

$\beta_{Most} \sim N(0, 1)$

$\beta_{NoMotivation} \sim N(0, 1)$

$\beta_{Most \times NoMotivation} \sim N(0, 1)$

$\Omega_{\mathbf{k}} \sim LKJ(1)$ where $\Omega_{\mathbf{k}}$ is a correlation matrix for group-level parameters which assumes all correlation matrices are equally likely.

We found that participants often did not seek more than one additional hint in our task (see Figure 6 below). As a consequence, there was little variance in responses, making it difficult to detect effects of either motivation or evidence. We subsequently performed analyses to determine what participants' behavior was like *when* they sought different amounts of information. These analyses revealed the same effects we observed in Experiments 1 and 2 (see Figure 7). However, Experiment 3 was rather uninformative with respect to the question of how motivation affects information-seeking behavior.

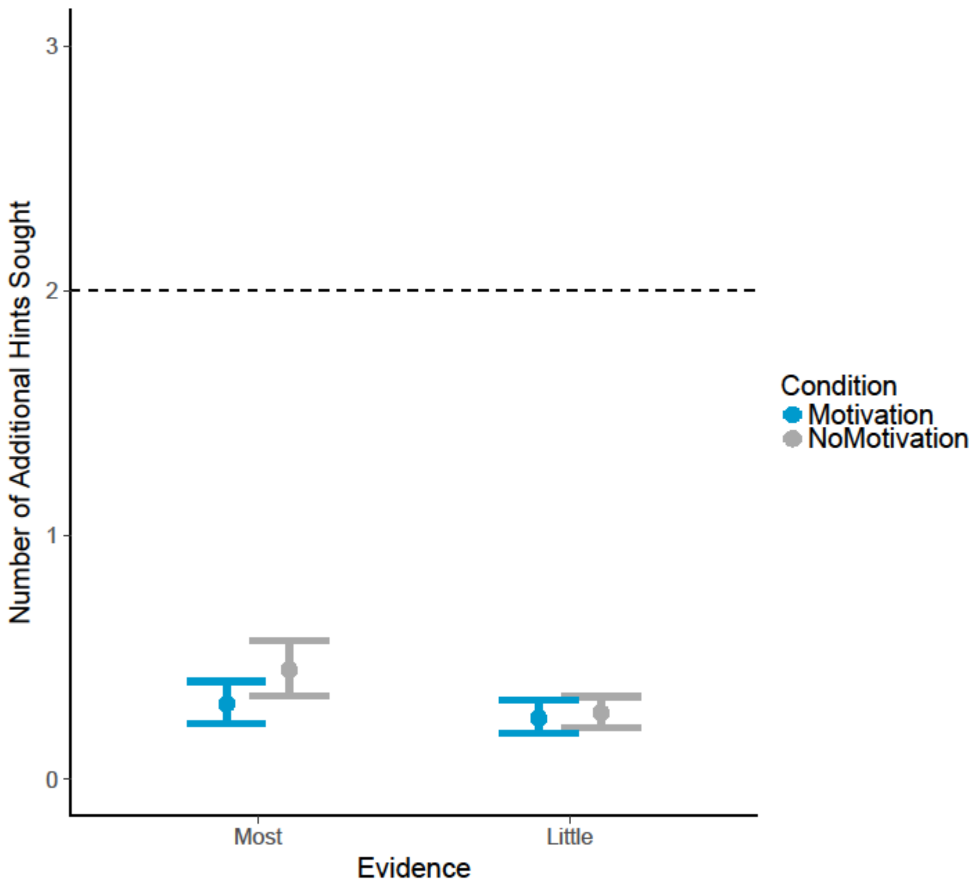


*Figure 6*. A marginal-effects plot of the number of hints participants sought across conditions in Experiment 3. Error bars represent 95% credible intervals. The dashed line represents the minimal amount of information required to make an informed choice in each condition. We found that participants sought only one additional hint across conditions.

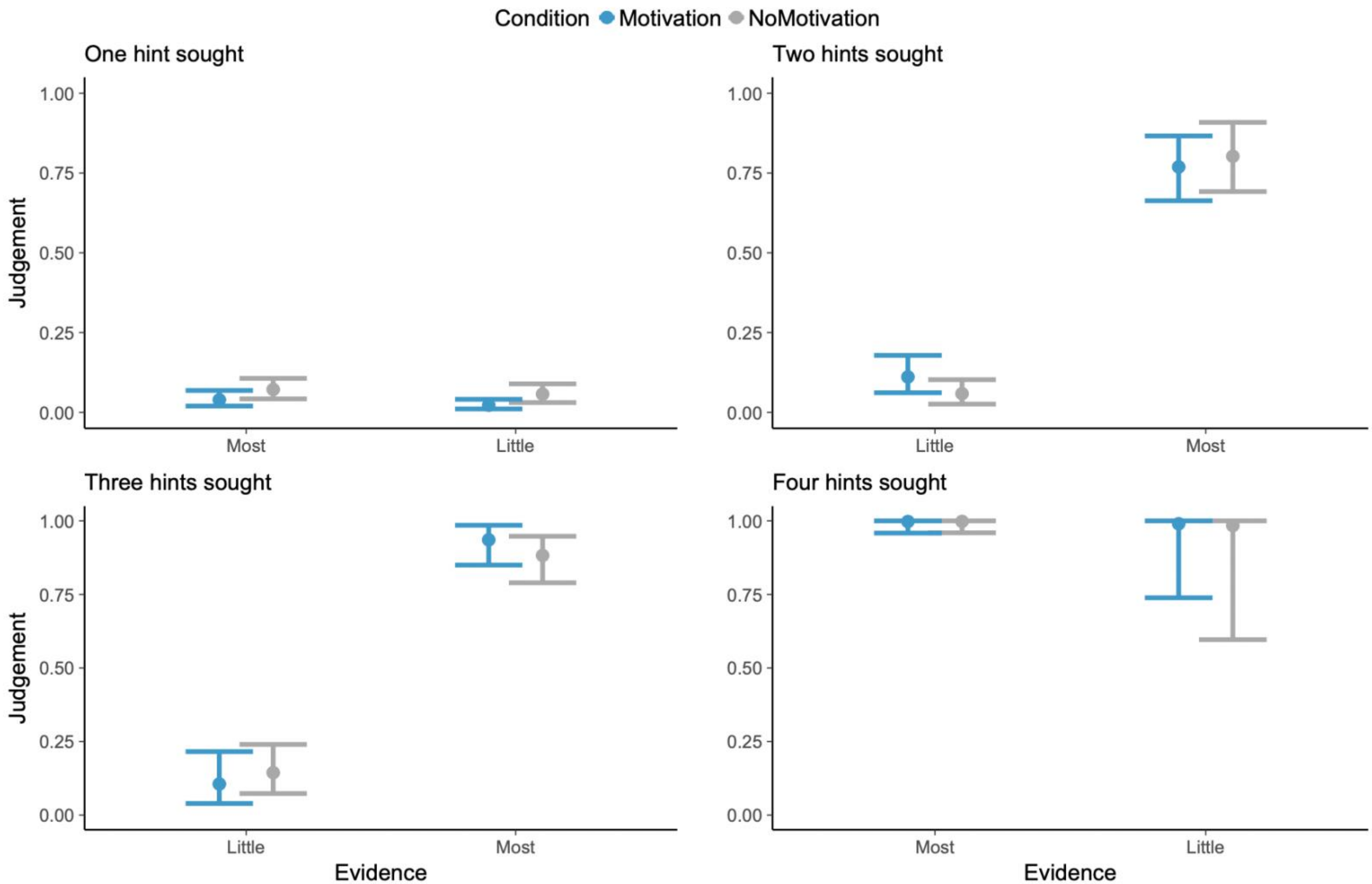


*Figure 7.* A marginal-effects plot of participants' judgments across conditions by the number of hints sought in Experiment 3. Error bars represent 95% credible intervals. We found that when participants sought two or more additional hints, they made decisions based on the evidence they received across condition.

## Discussion

The results from Experiments 1 to 3 suggest that participants did not behave in a biased way in a controlled judgment task aimed at testing how motivation affected reasoning. Taken together, these results provide preliminary support for the hypothesis that people are less biased than psychologists have traditionally inferred (Gershman, 2018; Griffiths & Tenenbaum, 2006; Tenenbaum, Griffiths, & Kemp, 2006; Jern, et al., 2014; Vul, Goodman, Griffiths, & Tenenbaum, 2014; Zimper & Ludwig, 2009). By making the learner's assumptions explicit, we can approximate many complex aspects of human reasoning such as how they assimilate information and make decisions when they are motivated. In our task, people sought less information before making a decision and misremembered the evidence presented, but their decisions were optimal *given* the information they had. From a cost-benefit analysis standpoint, we can establish that people differed in their assignment of costs and benefits associated with a given outcome and maximized utility in different ways depending on the task (see Griffiths & Tenenbaum, 2006). That is, in Experiments 1 and 2, people chose to maximize utility by choosing the bonus page more often when the evidence was ambiguous and in Experiment 3, they did so by sampling the minimal amount of information necessary to finish the task. Arguably, however, the lack of variance in responding in Experiment 3 is evidence that people did not actually attempt to perform the task making the data from Experiment 3 potentially uninformative.

Still, it is possible that because Experiments 1 and 2 in particular were entirely controlled, we did not target strongly-held beliefs or threaten people's identity in a way that would elicit motivated reasoning. That is, these effects might not replicate in a real-world scenario where people have strongly-held beliefs about areas related to their identity. Thus, the very nature of a controlled task might prohibit properly motivating people in a way that we could study the impact of motivation on evidence assimilation or information-seeking. One possible way to overcome this limitation is to study these same effects in children who are both, less likely to display inhibitory control (Carlson & Moses, 2001; Kochanska, Murray, Jacques, Koenig, & Vandegeest, 1996) and more likely to be affected by controlled rewards (Deci, 1971; Loveland & Olley, 1979). That is, in this population, we might be able to examine how motivation affects evidence assimilation in a more naturalistic setting (where there is a threat to their strongly-held beliefs) without losing experimental control. Thus, we conducted a series of studies mirroring Experiments 1 and 2 to examine the effect of motivation on evidence assimilation across development.

## Experiments 4 through 6:

## The Development of Evidence Assimilation

In Experiments 1 and 2, we found that people were motivated to win more points and chose the proposition that would maximize their reward even when the evidence ambiguously supported that proposition. However, it is possible that we did not detect motivated reasoning per se because participants were not sufficiently motivated by points in our task. Across three studies with children, we aimed to replicate our findings and created a similar motivated-reasoning paradigm to determine whether children—who are much more easily affected by external rewards (Deci, 1971; Loveland & Olley, 1979)—would exhibit motivated reasoning effects analogous to those taken from prior research in social psychology (e.g., Kundra & Sinclair, 2009; Mullen & Skitka, 2006). Prior work on motivated reasoning in children is suggestive—much like adults, children have been found to be insensitive to evidence that is inconsistent with what they want to believe (Klaczynski, 2000). Anecdotally, if we imagine a child who thinks they will get a toy when they win a game, it seems plausible that they might be motivated to reinterpret the rules of the game to make the chances that they win more probable (see Kunda, 1990). Indeed, empirical work in developmental psychology suggests that children regularly engage in wishful thinking and frequently overestimate their ability to perform difficult tasks (Levin, Yussen, Pressley, & de Rose, 1977; Schneider, 1998; Wellman, 1985; Yussen, & Levy, 1975; also see Kruger & Dunning, 1999). Consistent with the possibility of a disconnect between children's beliefs and the evidence for those beliefs, research with middle school adolescents has revealed that when children consider evidence for out-group beliefs, they exhibit polarization effects similar to those found in adults (Klaczynski, 2000). That is, children tend to ignore evidence inconsistent with what they want to believe (e.g., Nickerson, 1998).

This work may suggest that it is obvious that children will exhibit a higher degree of motivated reasoning biases than adults (Cialdini & Petty, 1981). However, some recent work suggests that drawing this conclusion may be too hasty. In the last ten years, several studies have provided evidence that even young children are capable of reasoning about causal relationships (Schulz, Gopnik, & Glymour, 2007), statistical evidence (Kushnir, Xu, & Wellman, 2010), and other complex distributions of evidence in ways that are consistent with rational-constructivist learning (Xu & Tenenbaum, 2007a, 2007b). For instance, children can use inductive inferences to guess the meaning of arbitrary words based solely on their prior experiences (Kushnir et al., 2010; also see Xu, & Tenenbaum, 2007a, 2007b). This suggests that children are able to follow evidence and make optimal decisions given a diversity of tasks.

Though these recent findings are compelling, they have not directly pitted a child's desired outcome against evidence supporting an opposing outcome in a controlled way. In the following experiments, we sought to examine children's responsiveness to different distributions of evidence using a simplified version of the task used in Experiments 1 and 2.

## Experiment 4

The categorization task used in this study was similar to Experiment 1 but had age-appropriate stimuli for children. Children were shown two pictures and given some hints about them. Their task was to decide which page was an instance of a novel category, for example, a "Blicket". Like in Experiments 1 and 2, hints were presented sequentially—for instance, the first hint participants received was, "The Blicket might be the one with red arrows," followed by the next hint that said, "The Blicket might be the one with the number eight," and so forth (see Figure 8 below). After all hints were presented within a trial, children were asked the categorization question (e.g., which one is the Blicket?). An abbreviated clip of one trial in the experiment can be viewed here.

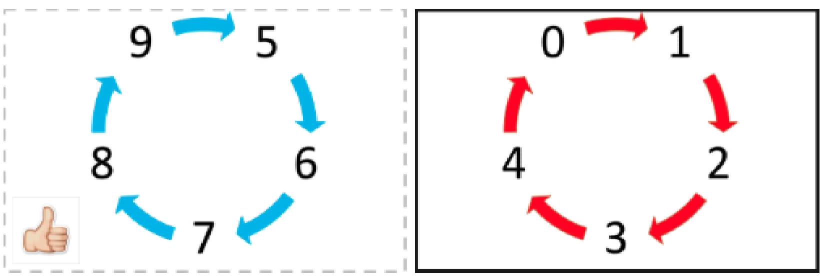


*Figure 8.* An example of stimuli used in Experiment 4, 5, and 6. The "bonus page" is indicated by the thumbs-up badge.

**Reward Structure.** As in Experiment 1, we manipulated the reward associated with choosing either the left or right page on the screen. We told children that scoring higher points would lead to winning more stickers in this task. Children were instructed that 1) they would win one sticker for choosing the correct response, 2) if the correct response *happened to be* the page with the thumbs-up badge and they chose it, then they would win three stickers, and 3) they would win no stickers for incorrect responses. Children were not given any feedback about their choices but were told that they would find out at the end of the study if their response was correct. Next, in order to pit their motivations against their desire to win more stickers, we manipulated the hints supporting the bonus page.

**Conditions.** As in Experiment 1, we created three conditions with different distributions of hints in a within-subjects design. In the Half condition, three of six hints supported the hypothesis that the bonus page was the correct response. In the Little condition, only one hint supported the hypothesis that the bonus page was the correct response. In the None condition, no hints supported the hypothesis that the bonus page was the correct response.

**Hypotheses**

We were interested in determining the mechanisms behind children's responses within a motivated-reasoning paradigm. Because children would be sufficiently motivated to earn more stickers, we hypothesized that in the Half condition, children would choose the bonus page more often even though the evidence itself would not clearly support this choice. In the Little condition, we hypothesized that children would still be motivated and choose the bonus page more often than the other page. That is, their responses in the Little condition would more closely resemble the Half condition than the None condition. In the None condition, we expected children to follow the hints and rarely choose the bonus page.

We further hypothesized that older children would be better at following the hints presented in this task compared to younger children. Also, we expected an Age × Condition interaction such that the slope of the condition effect would be different across Age.

## Preregistration and Analytic Approach

The sample size, predictions, and analysis scripts of our study were preregistered on the Open Science Framework. We conducted a power analysis to determine the sample size required to detect a Cohen's $d$ of .3 and so collected 100 participants from the Children's Museum of Phoenix. Children were allowed to participate only if their parents consented. Our analytic approach was similar to Experiment 1.

## Results

We tested whether children, who are more easily motivated by simple task-based rewards compared to adults, exhibited motivated reasoning. To test this hypothesis, we performed logistic regression predicting choices for the bonus page (1 = Chose bonus picture; 0 = Did not choose bonus picture) on the basis of Evidence (Reference = Half condition). This model included a group-level effect of Subject, Item and allowed for heterogeneity in the slope of the effect of evidence on participants' responses. Our model is specified below in the syntax of lme4 (Bates et al., 2015):

```
Response ~ 0 + intercept + Evidence + (1 + Evidence|Item) +
(1 + Evidence|Subject)
```

To model the joint probability distribution of participants' responses, we specified the following priors over the possible effects each variable could have on our response variable:

$\beta_0 \sim N(0,.75)$

$\beta_{Little} \sim N(-.4,.75)$

$\beta_{None} \sim N(-.4,.75)$

$sd_{\forall_x} \sim N(1,3)$ where $x$ is a group-level effect

$\Omega_{\mathbf{k}} \sim LKJ(1)$ where $\Omega_{\mathbf{k}}$ is a correlation matrix for group-level parameters which assumes all correlation matrices are equally likely.

The posterior regression coefficients for this analysis represent participants' responses across conditions and are shown in Figure 9 below. Our results replicated the main findings from Experiments 1 and 2: In general, children made choices on the basis of the evidence presented and they chose the bonus page more often in the Half condition compared to the other two conditions. Further, children's choices in the Little condition depicted some extent of motivated reasoning but were similar to the None condition than to the Half condition (see Figure 9) which was inconsistent with our preregistered hypothesis. These results suggest that children, who were motivated to win more stickers, chose the bonus page more often in the Half condition even though the evidence only ambiguously supported this choice but they did not go unreasonably beyond the evidence by choosing the bonus page even when very little evidence supported that choice.

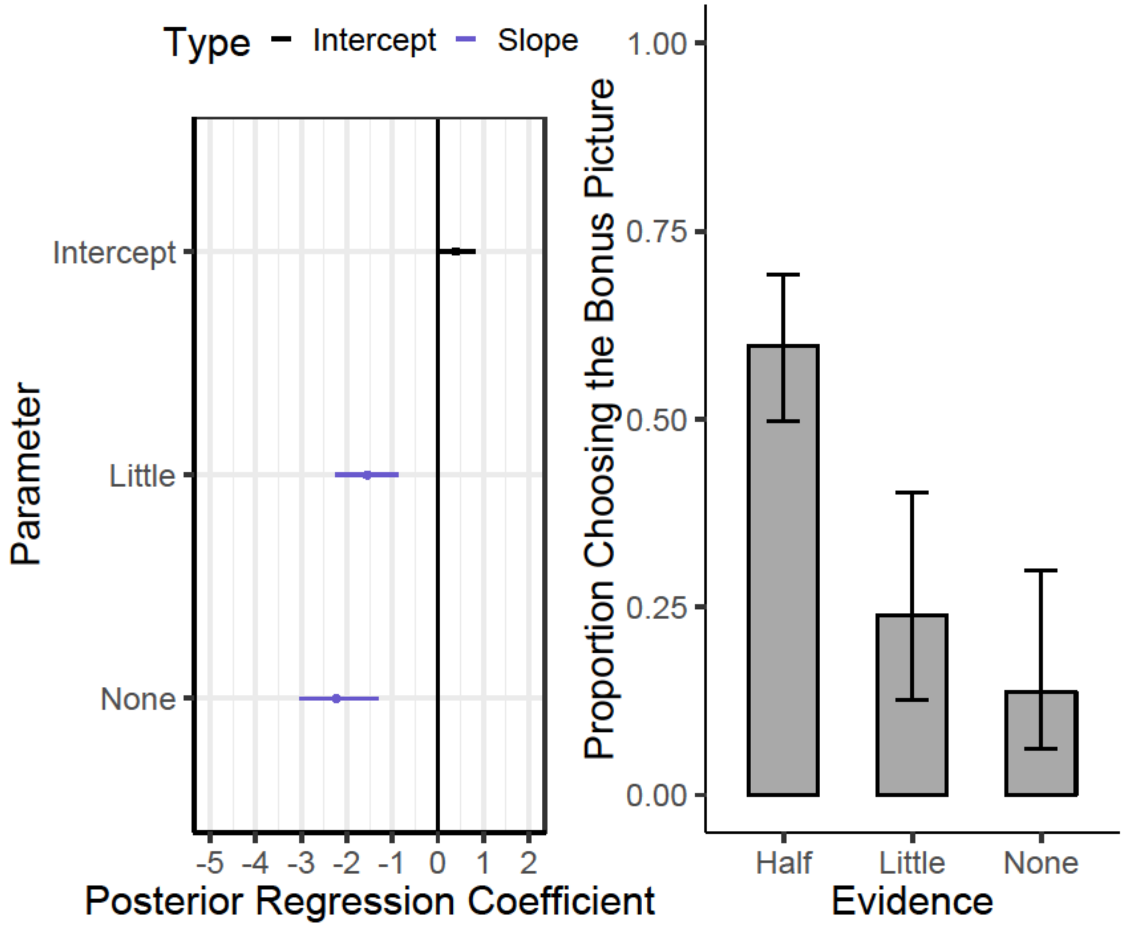


*Figure 9*. The posterior regression coefficients (left) and a bar graph (right) of the proportion of choices for the bonus page across conditions in Experiment 4. Relative to the Half condition, children chose the bonus page less often in the other two conditions.

Next, we tested and observed the predicted Age × Evidence interaction (see Figure 10 below). This linear regression model also included a group-level effect of Subject, Item and allowed for heterogeneity in the slope of the interaction and the effect of evidence on participants' responses. Our model is specified below in the syntax of lme4 (Bates et al., 2015):

```
Response ~ 0 + intercept + Age*Evidence + (1 + Age*Evidence|Item)
+ (1 + Evidence|Subject)
```

To model the joint probability distribution of participants' responses, we specified the following priors over the possible effects each variable could have on our response variable:

$\beta_0 \sim N(0, .75)$

$\beta_{Age} \sim N(0, .5)$

$\beta_{None} \sim N(-.4, .75)$

$\beta_{Little} \sim N(-.4, .75)$

$\beta_{Age \times None} \sim N(-.1, .5)$

$\beta_{Age \times Little} \sim N(-.1, .5)$

$sd_{\forall_x} \sim N(1, 3)$ where $x$ is a group-level effect

$\Omega_{\mathbf{k}} \sim LKJ(1)$ where $\Omega_{\mathbf{k}}$ is a correlation matrix for group-level parameters which assumes all correlation matrices are equally likely.

The posterior regression coefficients for this analysis represent participants' responses across Age and Evidence, as shown in Figure 10 below. Older children were more responsive to the available evidence than younger children and chose the bonus page less often in the Little and None conditions. Comparatively, in the Half condition, older children chose the bonus page about as often younger children.

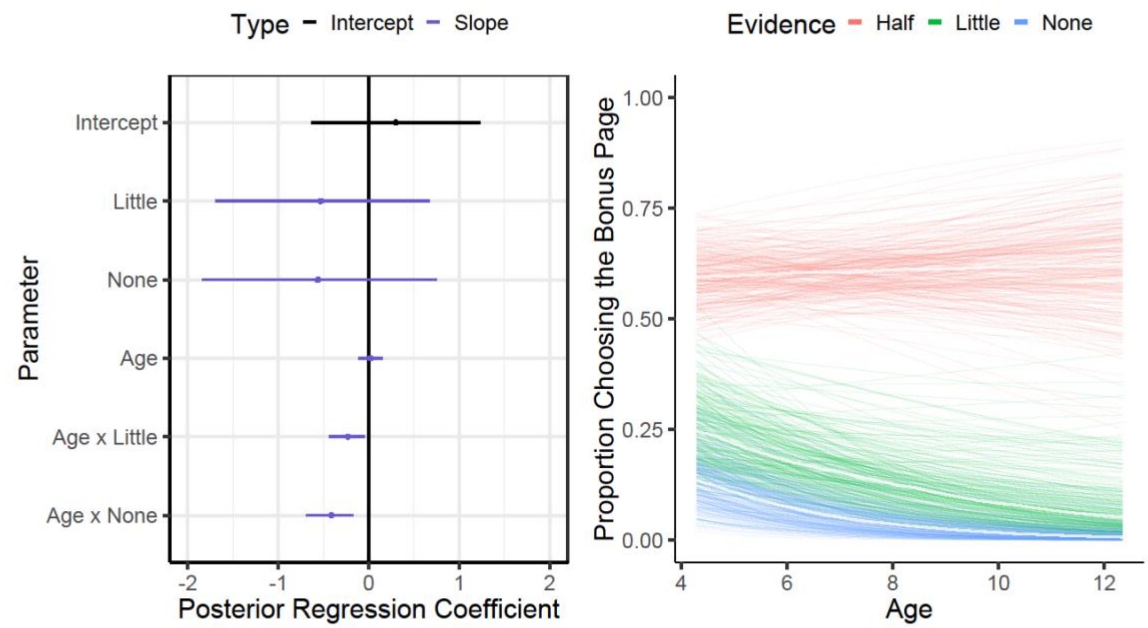


*Figure 10.* The posterior regression coefficients (left) and a spaghetti plot (right) of the effect of Evidence on choices varying by the age of the participant in Experiment 4. Older children were better at following the evidence and chose the bonus page less often than younger children in the Little and None conditions.

Although children appear to behave in similar ways as adults, it is possible that their overall patterns do not represent maximization of utility. For instance, children may not be appropriately choosing based on the evidence they remember or may systematically misremember evidence for the bonus page when there is no evidence. Further, given that data from children is inherently noisier, developmental trends need to be treated with considerable caution. Consequently, we sought to replicate and extend the results of this experiment in Experiment 5.

## Experiment 5

We made two changes to the task from Experiment 4: First, we changed the prize from stickers to tickets, which children could exchange for a prize at the end of the task. This ensured that children were really motivated to win a larger reward in this task (it is possible, for instance, that children exhibit substantial diminishing returns on stickers). Second, to check whether children remembered the hints correctly, we added a memory question (similar to the question used in Experiment 2). This question asked children to report the number of hints they remembered in support of the bonus page at the end of each trial. An abbreviated clip of one trial in the experiment can be viewed here.

### Hypotheses

While intriguing, the patterns observed in Experiment 4 do not directly reveal the mechanisms underlying children's choices. Experiment 5 sought to resolve this issue. In light of the results of Experiment 4, we hypothesized that in the Half condition children would choose the bonus page more often. In the Little and None conditions, we expected children to follow the hints and choose the bonus page less often than the other page. For the memory question, we were unsure about the extent to which children would misremember the amount of hints presented and so, we hypothesized that their choices would be based on the amount of hints they remembered across all conditions.

### Preregistration and Analytic Approach

The sample size, predictions, and analysis scripts of our study were preregistered on the Open Science Framework. We collected data from 50 participants from the Children's Museum of Phoenix after gaining consent from their parents. Our analytic approach was the same as Experiment 4.

**Results**

As in Experiment 4, conducted logistic regression predicting choices for the bonus page (1 = Chose bonus picture; 0 = Did not choose bonus picture) on the basis of Evidence (Reference = Half condition) and found that children chose the bonus page more often in the Half condition compared to the Little and None conditions (see Figure 11 below). This model included a group-level effect of Subject, Item and allowed for heterogeneity in the slope of the effect of evidence on participants' responses. Our model is specified below in the syntax of lme4 (Bates et al., 2015):

```
Response ~ 0 + intercept + Evidence + (1 + Evidence|Item) +
(1 + Evidence|Subject)
```

To model the joint probability distribution of participants' responses, we specified the following priors over the possible effects each variable can have on our response variable:

$\beta_0 \sim N(0, .75)$

$\beta_{None} \sim N(-.4, .75)$

$\beta_{Little} \sim N(-.4, .75)$

$sd_{\forall_x} \sim N(1, 3)$ where $x$ is a group-level effect

$\Omega_{\mathbf{k}} \sim LKJ(1)$ where $\Omega_{\mathbf{k}}$ is a correlation matrix for group-level parameters which assumes all correlation matrices are equally likely.

The posterior regression coefficients for this analysis represent participants' responses across conditions, as shown in Figure 11 below. In the None condition, children followed the evidence and chose based on the hints presented but in the Little condition they chose the bonus page more often. Hence, we replicated the main effects from prior experiments: children generally followed the evidence and the motivation to win a larger reward in the Half condition led children to go beyond the evidence and choose the bonus page.

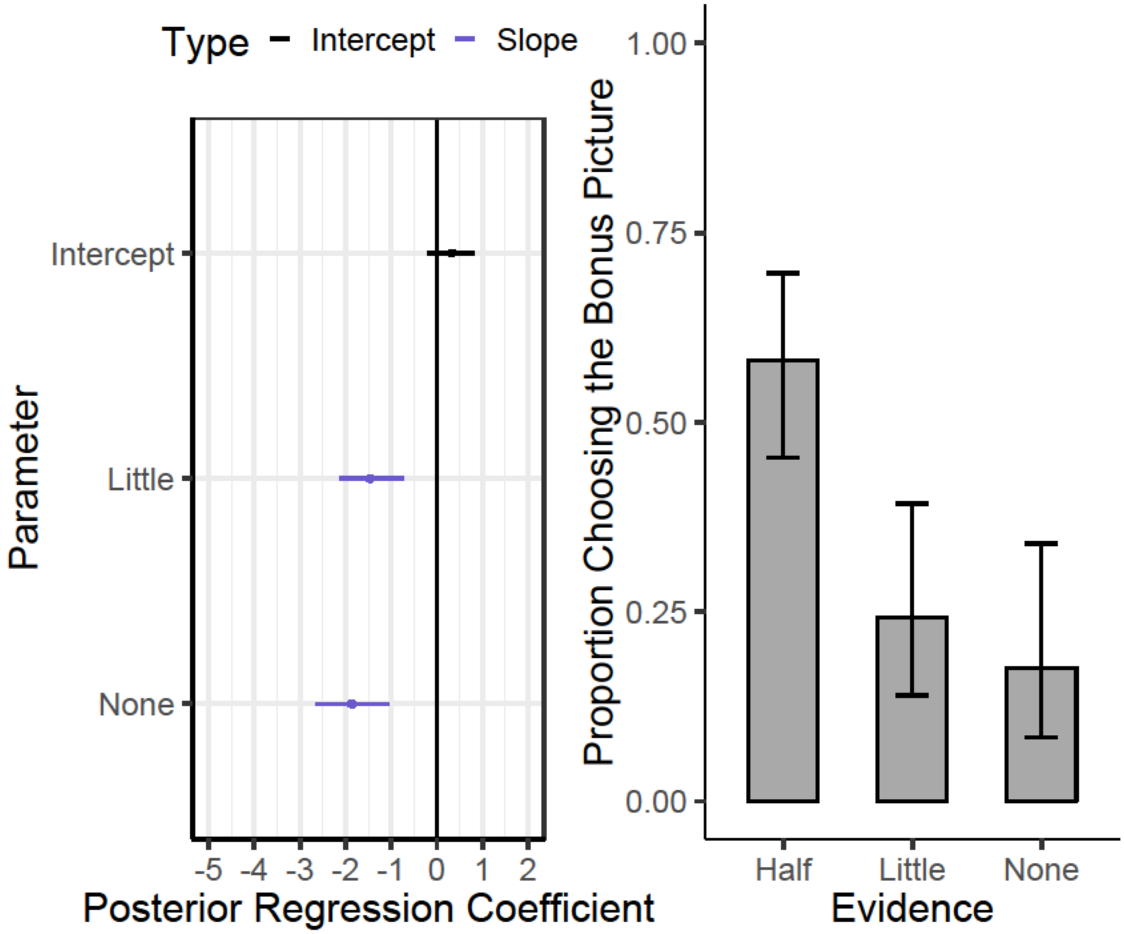


*Figure 11*. The posterior regression coefficients (left) and a bar graph (right) of the proportion of choices for the bonus page across conditions in Experiment 5. This is a direct replication of the findings from Experiment 4 wherein children chose the bonus page more often in the Half condition compared to the other two conditions.

As in Experiment 4, we again checked for an Age × Evidence interaction and found that older children were better at following the evidence than younger children (see Figure 12). This model also included a group-level effect of Subject, Item and allowed for heterogeneity in the slope of the interaction and the effect of evidence on participants' responses. Our model is specified below in the syntax of lme4 (Bates et al., 2015):

```
Response ~ 0 + intercept + Age*Evidence + (1 + Age*Evidence|Item)
+ (1 + Evidence|Subject)
```

To model the joint probability distribution of participants' responses, we specified the following priors over the possible effects each variable can have on our response variable:

$\beta_0 \sim N(0, .75)$

$\beta_{Age} \sim N(0, .5)$

$\beta_{None} \sim N(-.4, .75)$

$\beta_{Little} \sim N(-.4, .75)$

$\beta_{Age \times None} \sim N(-.1, .5)$

$\beta_{Age \times Little} \sim N(-.1, .5)$

$sd_{\forall_x} \sim N(1, 3)$ where $x$ is a group-level effect

$\Omega_{\mathbf{k}} \sim LKJ(1)$ where $\Omega_{\mathbf{k}}$ is a correlation matrix for group-level parameters which assumes all correlation matrices are equally likely.

The posterior regression coefficients for this analysis represent participants' responses across age and condition, as shown in Figure 12 below.

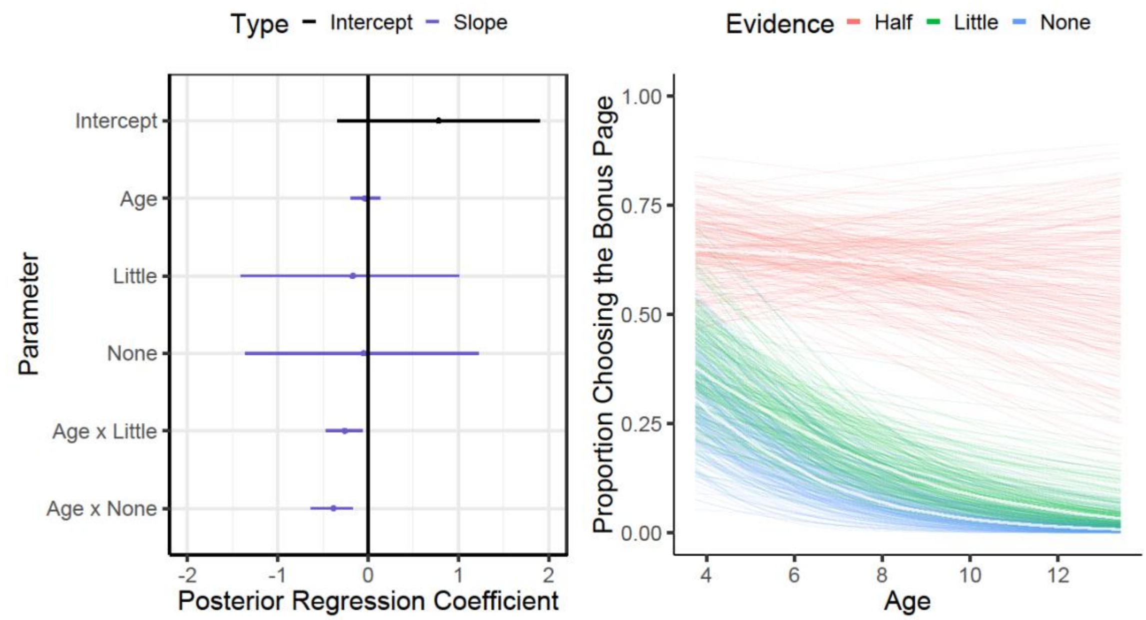


*Figure 12.* The posterior regression coefficients (left) and a spaghetti plot (right) of the effect of Evidence on choices varying by the age of the participant in Experiment 5. Older children were better at following the evidence and chose the bonus page less often than younger children in the Little and None conditions.

Next, we examined whether children's memory for the hints presented was affected by their motivations. We conducted ordinal regression predicting memory for the bonus page (0 = No hints supporting the bonus page; 6 = Six hints supporting the bonus page) on the basis of Evidence (Reference = Half condition). This model included a group-level effect of Subject and allowed for heterogeneity in the slope of the effect of evidence on participants' responses. Our model is specified below in the syntax of lme4 (Bates et al., 2015):

```
Memory ~ Evidence + (1 + Evidence|Subject)
```

To model the joint probability distribution of participants' responses, we specified the following priors over the possible effects each variable could have on our response variable:

$\beta_{Intercept[1]} \sim N(-2.19, .5)$

$\beta_{Intercept[2]} \sim N(-1.38, .5)$

$\beta_{Intercept[3]} \sim N(-.61, .5)$

$\beta_{Intercept[4]} \sim N(.61, .5)$

$\beta_{Intercept[5]} \sim N(1.38, .5)$

$\beta_{Intercept[6]} \sim N(2.19, .5)$

$\beta_{None} \sim N(-1, 1)$

$\beta_{Little} \sim N(-1, 1)$

$sd_{\forall_x} \sim N(1, 3)$ where $x$ is a group-level effect

$\Omega_{\mathbf{k}} \sim LKJ(1)$ where $\Omega_{\mathbf{k}}$ is a correlation matrix for group-level parameters which assumes all correlation matrices are equally likely.

The posterior regression coefficients for this analysis represent participants' responses to the memory question across conditions, as shown in Figure 13 below. This analysis indicated that children misremembered the amount of evidence presented across trials (see Figure 13). Specifically, children misremembered more hints in support of the bonus page which suggests that children displayed motivated reasoning to some extent in our task and may have misremembered evidence to support their desired outcome. However, as with Experiment 1, it is likely that this seemingly systematic tendency to misremember evidence for the bonus page may be due to the response scale rather than the presence of motivation per se.

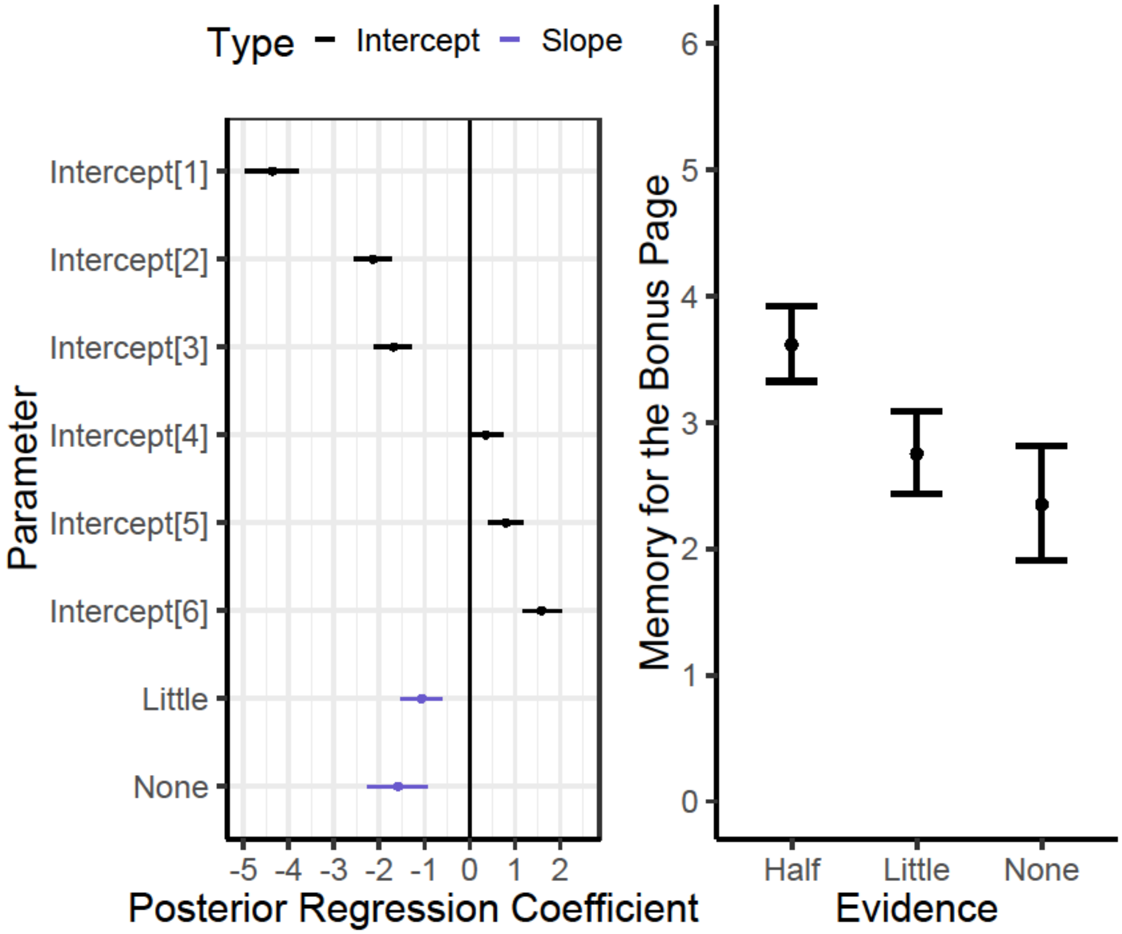


*Figure 13.* The posterior regression coefficients (left) and a marginal-effects plot (right) of children's memory for the bonus page across conditions in Experiment 5. Error bars represent 95% credible intervals. Children's memory for the bonus page was inaccurate across all conditions.

Remarkably, young children exhibited decision-making behavior similar to that of adults. We found that young children generally made categorization choices based on the evidence presented but when the evidence was ambiguous, they went much beyond the evidence and chose to win a larger reward. In situations where the evidence was ambiguous, children showed a tendency (though it was weaker than adults) to choose the bonus page presumably with the aim of maximizing their reward. These results provide support for the hypothesis that people are less biased than once believed, as children made decisions to maximize utility (Kahneman & Egan, 2011). Still, memory for the hints presented was biased towards the bonus page and this could be support for motivated reasoning. Were children's choices indicative of motivated reasoning in the Half condition? To clarify, we conducted another experiment using a modified version of our categorization task.

## Experiment 6

In this experiment, we sought to replicate previous findings and determine whether children were biased in our task. To do this, we kept the reward structure the same as in Experiments 4 and 5 but created a task similar to Experiment 2: First, we added a Control condition where neither of the pages would lead to a bonus prize if children selected it as their response. This would help us compare their responses in the Motivation condition with the Control condition and determine whether children's memory was affected due to their motivation to win a larger prize. That is, if there was systematic misremembering of the evidence in the Motivation condition, then that would be evidence for motivation affecting evidence assimilation rather than evidence of utility maximization. Second, we replaced the None condition (where no hints supported the bonus page) with a Most condition (where five of six hints supported the bonus page) in the Motivation condition as in Experiment 2. The Most condition would allow us to confirm whether children were behaving as they should in this task. The trials in the Control condition mirrored those from the Motivation condition. Hence, this experiment had a 2 (Motivation condition, Control condition) x 3 (Half condition, Little condition, Most condition) within-subjects design. An example of a trial from the Motivation condition can be found here and from the Control condition can be found here.

### Hypotheses

Experiments 1 through 5 provide consistent support for the hypothesis that people are less biased in their reasoning than previously believed. Consequently, in the Motivation condition in Experiment 6, we hypothesized that even though the evidence was ambiguous, children would want to maximize their reward and choose the bonus page more often in the Half condition. In the Little and Most conditions, we hypothesized that children would follow the evidence and choose accordingly—they would pick the bonus page more often in the Most condition and less often in the Little condition. Because there was no motivation for children to pick either of the pages more often in the Control condition, we hypothesized that they would follow the hints presented and choose accordingly across all trials.

We also predicted that there would be an Age × Evidence interaction such that the slope of Evidence (that is, the Little, None, and Most conditions) would be different across age. Based on Experiment 5, we hypothesized that children's memory would be inaccurate and that this would influence their choices. We did not know whether misremembering would be more systematic in the Motivated condition compared to the Control condition but hypothesized that memory would direct children's choices in this task.

**Preregistration and Analytic Approach**

The sample size, predictions, and analysis scripts of our study were preregistered on the Open Science Framework. We conducted a power analysis to determine the sample size required to detect a Cohen's *d* of .3 and so collected 100 participants from the Children's Museum of Phoenix. Children were allowed to participate only if their parents consented. The analytic approach was similar to Experiment 2.

**Results**

We tested whether children's choices differed in the Motivation condition compared to the Control condition. Specifically, we tested whether children's responses would differ in the Half condition. We conducted logistic regression predicting children's choices for the bonus page on the basis of Evidence (Half, Little, Most), Condition (Motivation, Control), and their interaction (Reference = Half-Motivation condition). This model included a group-level effect of Subject and allowed for heterogeneity in the slope of the interaction on participants' responses. Our model is specified below in the syntax of lme4 (Bates et al., 2015):

```
Response ~ 0 + intercept + Evidence*Condition +
(1 + Evidence*Condition|Subject)
```

To model the joint probability distribution of participants' responses, we specified the following priors over the possible effects each variable could have on our response variable:

$\beta_0 \sim N(0, .75)$

$\beta_{Little} \sim N(.62, .75)$

$\beta_{Most} \sim N(-.62, .75)$

$\beta_{NoMotivation} \sim N(0, .5)$

$\beta_{Little \times NoMotivation} \sim N(0, .5)$

$\beta_{Most \times NoMotivation} \sim N(0, .5)$

$sd_{\forall_x} \sim N(1, 3)$ where $x$ is a group-level effect

$\Omega_{\mathbf{k}} \sim LKJ(1)$ where $\Omega_{\mathbf{k}}$ is a correlation matrix for group-level parameters which assumes all correlation matrices are equally likely.

The posterior regression coefficients for this analysis represent participants' responses across conditions and are shown in Figure 14 below. We found data strikingly similar to those results in Experiment 2: In the Motivation condition, children chose the bonus page more often than in the Control condition—so motivation exerted a considerable effect on children's decisions. However, in general, their choices mirrored adults' choices given the relevant evidence (though perhaps not perfectly, given that motivation seemed to lead children to choose the bonus page more than was likely warranted in the Little condition).

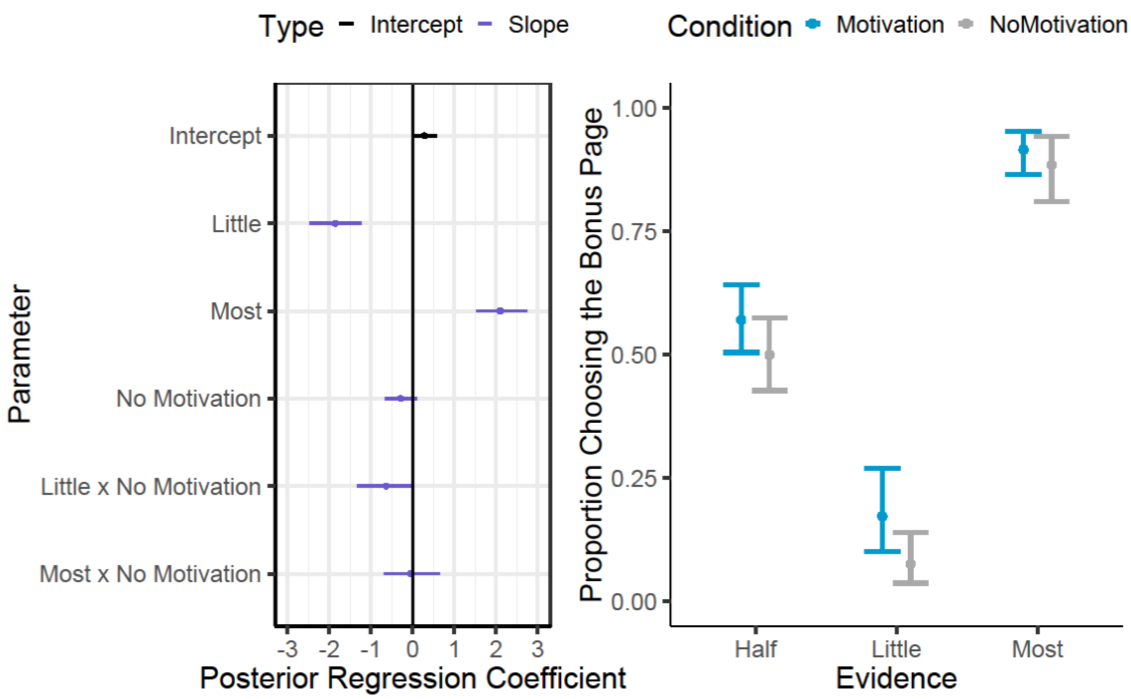


*Figure 14.* The posterior regression coefficients (left) and a marginal-effects plot (right) of the proportion of choices for the bonus page across conditions in Experiment 6. Error bars represent 95% credible intervals. Children chose the bonus page more often in the Motivation condition than the Control condition.

We also tested how children's pattern of responding shifted across development based on the presence or absence of motivation i.e., an Age × Evidence × Condition interaction and found that older children were better at following the evidence than younger children across conditions (see Figure 15). This model also included a group-level effect of Subject and allowed for heterogeneity in the slope of the Evidence ×

Condition interaction on participants' responses. Our model is specified below in the syntax of lme4 (Bates et al., 2015):

```
Response ~ 0 + intercept + Age*Evidence*Condition +
(1 + Evidence*Condition|Subject)
```

To model the joint probability distribution of participants' responses, we specified the following priors over the possible effects each variable can have on our response variable:

$\beta_0 \sim N(0, .75)$

$\beta_{Age} \sim N(0, .5)$

$\beta_{Little} \sim N(.62, .75)$

$\beta_{Most} \sim N(-.62, .75)$

$\beta_{NoMotivation} \sim N(0\ .75)$

$\beta_{Age \times Little} \sim N(-.1, .5)$

$\beta_{Age \times Most} \sim N(.1, .5)$

$\beta_{Age \times NoMotivation} \sim N(0, .5)$

$\beta_{Little \times NoMotivation} \sim N(0, .5)$

$\beta_{Most \times NoMotivation} \sim N(0, .5)$

$\beta_{Age \times Little \times NoMotivation} \sim N(0, .5)$

$\beta_{Age \times Most \times NoMotivation} \sim N(0, .5)$

$sd_{\forall_x} \sim N(1, 3)$ where $x$ is a group-level effect

$\Omega_{\mathbf{k}} \sim LKJ(1)$ where $\Omega_{\mathbf{k}}$ is a correlation matrix for group-level parameters which assumes all correlation matrices are equally likely.

The posterior regression coefficients for this analysis represent participants' responses across age, evidence, and condition, as shown in Figure 15 below. We found that older children (compared to younger children) were better at following the evidence but this tendency did not materially differ regardless of condition, suggesting that the effects of motivation on responding did not interact with the Age by Evidence interaction we previously observed.

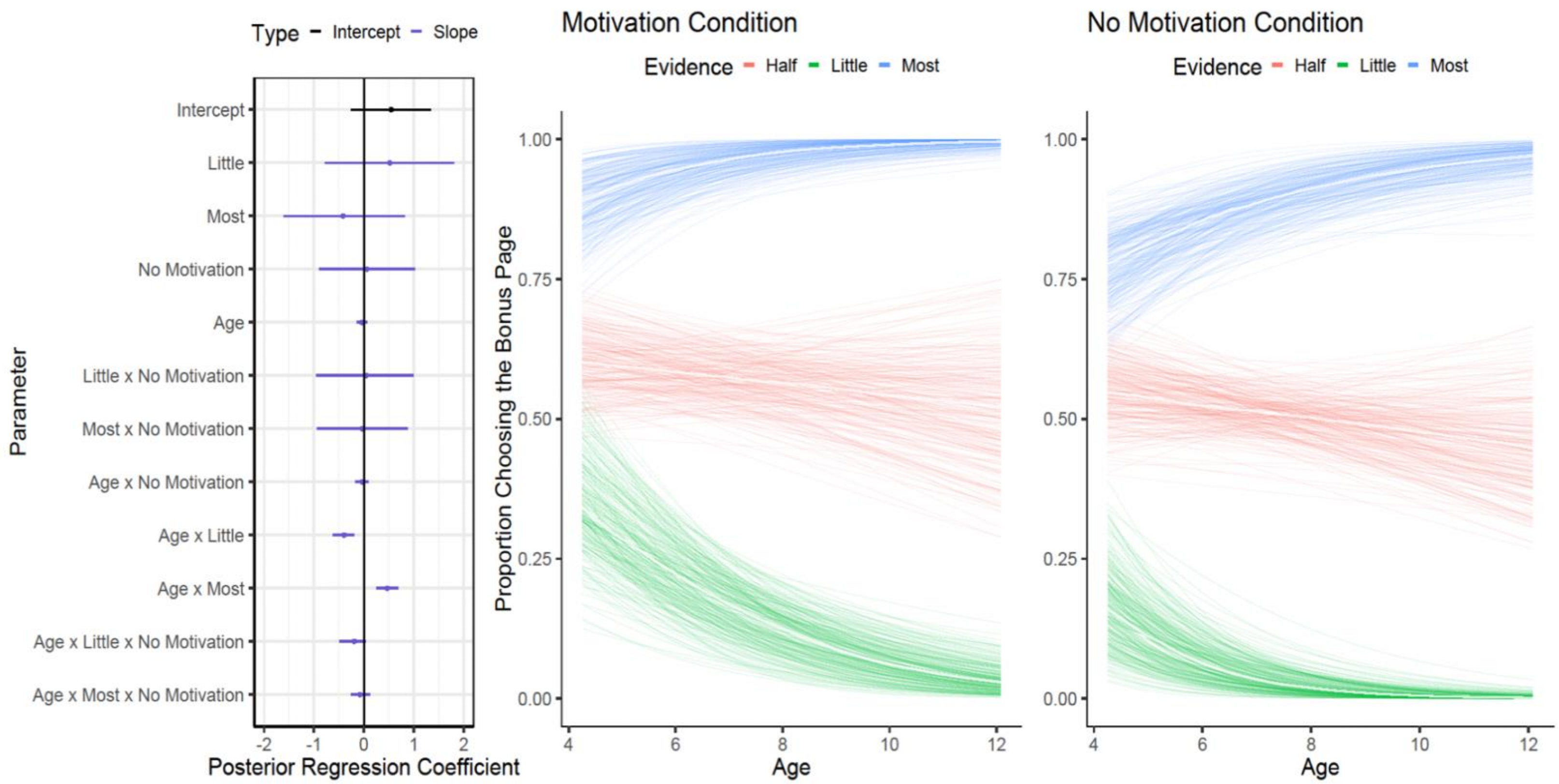


*Figure 15.* The posterior regression coefficients (left) and a spaghetti plot (right) of the effect of Condition on choices varying by the age of the participant in Experiment 6. We compared participants’ responses in the Motivation condition to the Control condition. Older children were better at following the evidence and chose based on the hints presented across condition.

Finally, we conducted ordinal regression predicting memory for the bonus page (0 = No hints supporting the bonus page; 6 = Six hints supporting the bonus page) across Evidence × Condition (Reference = Half-Motivation condition). This model included a group-level effect of Subject and allowed for heterogeneity in the slope of the interaction on participants' memory. Our model is specified below in the syntax of lme4 (Bates et al., 2015):

```
Memory ~ Evidence*Condition + (1 + Evidence*Condition| Subject)
```

To model the joint probability distribution of participants' responses, we specified the following priors over the possible effects each variable could have on our response variable:

$\beta_{Intercept[1]} \sim N(-2.19, .5)$

$\beta_{Intercept[2]} \sim N(-1.38, .5)$

$\beta_{Intercept[3]} \sim N(-.61, .5)$

$\beta_{Intercept[4]} \sim N(.61, .5)$

$\beta_{Intercept[5]} \sim N(1.38, .5)$

$\beta_{Intercept[6]} \sim N(2.19, .5)$

$\beta_{Little} \sim N(-1,1)$

$\beta_{Most} \sim N(1, 1)$

$\beta_{NoMotivation} \sim N(0, 1)$

$\beta_{Little \times NoMotivation} \sim N(0, 1)$

$\beta_{Most \times NoMotivation} \sim N(0, 1)$

$sd_{\forall_x} \sim N(1, 3)$ where $x$ is a group-level effect

$\Omega_{\mathbf{k}} \sim LKJ(1)$ where $\Omega_{\mathbf{k}}$ is a correlation matrix for group-level parameters which assumes all correlation matrices are equally likely.

The posterior regression coefficients for this analysis represent participants' responses to the memory question across conditions, as shown in Figure 16 below. We found that like adults, children misremembered the hints supporting the bonus page but this tendency was not systematic and was unrelated to the presence or absence of motivation.

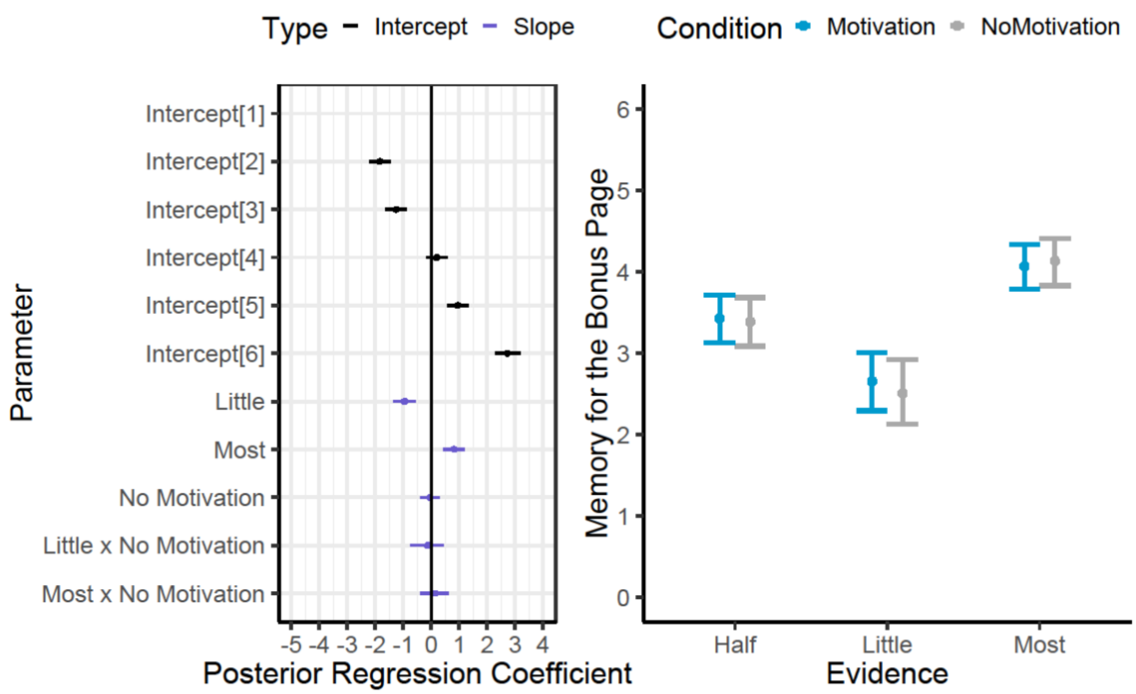


*Figure 16.* The posterior regression coefficients (left) and a marginal-effects plot (right) of the memory for the bonus page across conditions in Experiment 6. Error bars represent 95% credible intervals. Children's memory for the bonus page was inaccurate across all conditions.

In summary, Experiment 6 replicated our prior findings and observed effects remarkably consistent with the data we observed from our studies with adult participants. Namely, even for children who were motivated at the prospect of winning a prize, we observed decisions made largely based on the evidence presented and children chose to maximize their reward when there was ambiguous evidence in the Motivation condition.

## General Discussion

These studies used a controlled task to examine whether people can effectively assimilate evidence within a motivated-reasoning context. We created a simple judgement task wherein participants were presented two propositions and had to determine which one was the correct response based on hints about the propositions. We motivated participants by instructing them that if they picked the correct response (i.e., the proposition characterized with the most supporting evidence) and this response happened to have a badge on it (for instance, a thumbs-up badge), that they would win bonus points. We manipulated the number of hints supporting this "bonus" proposition and found that people were good at assimilating evidence and making decisions based on the hints they received regardless of their motivations. Moreover, across five experiments we found that both, children and adults, behaved similarly when the evidence was ambiguous—they chose to maximize their reward despite remembering that there was insufficient evidence supporting this choice.

Taken together, these results provide preliminary support for rethinking the assumption that human cognition is inherently biased and prone to error. Rather, our data suggest that in a controlled task where the reward structure and evidence is known, both adults and children follow the evidence and maximize utility in ways that accord with optimal performance. Under this conception of human reasoning, we must understand people's prior beliefs in order to assess whether they deviate from optimal performance. For instance, under a Bayesian framework it would seem highly likely that a person who holds conservative political beliefs will support the position that the death penalty is an effective deterrent of crime (Zeisel & Gallup, 1989). Such a Bayesian view also assumes that humans are rational agents who can update their prior beliefs in a logical way to form a revised posterior set of beliefs. Consequently, belief polarization in response to ambiguous evidence is considered an irrational response within such a framework because it assumes that people are capable of revising their beliefs in optimal ways. In our task, participants could not simply select a “correct response” when there was ambiguous evidence, so choosing the bonus proposition as the correct response was the optimal choice. Further, when participants had the chance to obtain more information and chose to do so, their choices were optimal given the information they had. Much recent work suggests that seemingly irrational behaviors often stem from coherent belief networks and that people are better at assimilating evidence than previously believed (Edwards, 1954; Gershman, 2018; Jern et al., 2014; Kahneman & Egan, 2011; Vul et al., 2014). Though participants initially appeared biased in our task, their choices reflected a desire to maximize utility rather than motivated reasoning.

Participants’ selection of the bonus page differed based on age: Older children followed the evidence better than younger children and chose the bonus considerably less often than younger children. Moreover, children misremembered the hints presented in this task and their memory affected their responses across conditions—if they remembered more hints supporting a proposition, then they chose that proposition more often. Given that children have limited memory capacities (Handley, Capon, Beveridge, Dennis, & Evans, 2004; Swanson, 1996) and adopt more conservative decision criteria than young adults (Ratcliff, Love, Thompson, & Opfer, 2012), these results suggest that children can reason using a “rational-constructivist” approach—the type of learning that uses probabilistic models of reasoning (Griffiths, Chater, Kemp, Perfors, & Tenenbaum, 2010; Gerken, 2010; Kushnir et al., 2010; Xu & Denison, 2009; Xu & Garcia, 2008; Xu & Kushnir, 2013). That is, children are able to rapidly integrate new evidence with prior beliefs and can revise their decisions optimally. Though there was no correct response in some trials within our task, children were effectively able to maintain multiple hypotheses about the correct response and provide an optimal judgement based on the hints presented across trials. Hence, these studies provide valuable insight into the developmental trajectory of evidence assimilation and can be used to understand important aspects of decision-making such as reasoning under uncertainty.

Using a controlled task allowed us to firmly establish these findings as we were able to manipulate the evidence and the reward participants received. Participants chose to maximize utility to win a larger reward. Even so, we did not target strongly-held beliefs on issues closely related to people's identity such as religion or political affiliation. Such strongly-held beliefs can affect decision-making in that they help reaffirm an individual's sense of group identity (Kahan, et al., 2012). From a group-identity perspective, biased reasoning has little to do with conscious information avoidance or biased assimilation but stems from coherent belief networks. Our task suggests that people did not deliberately ignore the fact that there was ambiguous evidence but chose to maximize utility because it was the optimal choice. However, many aspects remain unclear: for instance, how do people integrate new evidence and revise their beliefs? Are people biased in their information search within a motivated-reasoning context? Future work in this area should focus on detecting the mechanisms underlying these decisions. Such an evaluation can guide belief-change researchers and interventionists to better understand the basis of people's decisions regarding important social, moral, and political issues.

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